Deconstructing Retrieval Abilities of Language Models

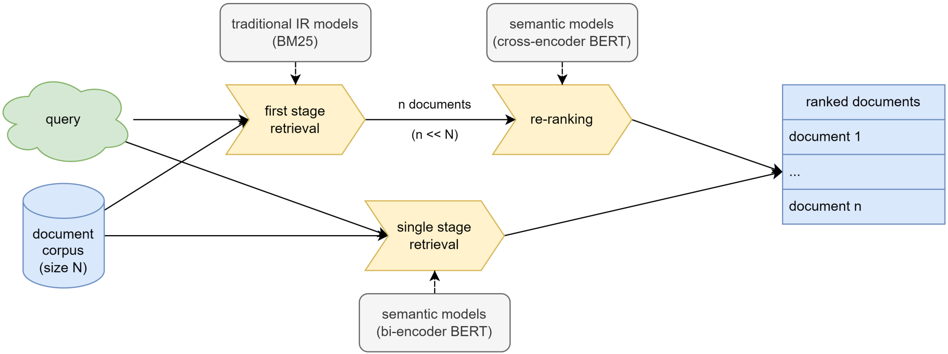
Hauke Tristan Hinrichs

Faculty of Electrical Engineering and Computer Science
Institute of Data Science
Department of Knowledge-based Systems
L3S Research Center

July 3, 2023

Motivation

- Information Retrieval (IR) decides which information is presented to us

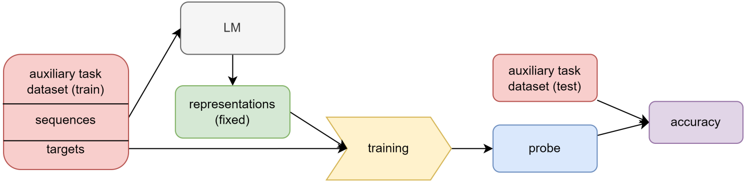


[1–3]

- Goal: shed light on inner workings of bi-encoder TCT-ColBERT [4, 5]

Motivation – Probing

- Probing: technique to *probe* for encoded information in the representations of language models (LMs) [6–8]

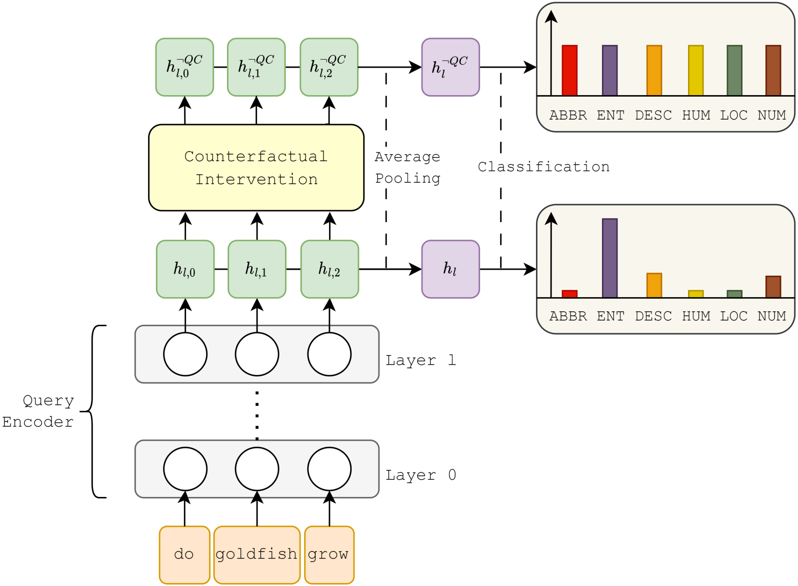


- Problem: encoding of information no proof for usage [9]
- *Causal Probing*: enabling causal explanations for model behavior by extending probing [10]

Research Questions

- **RQ1** Can we confirm the feasibility of *causally probing* our bi-encoder subject model in the context of retrieval?
- **RQ2** On which properties does our bi-encoder rely upon to solve the task of text retrieval?
- **RQ3** At which layers are important properties encoded?

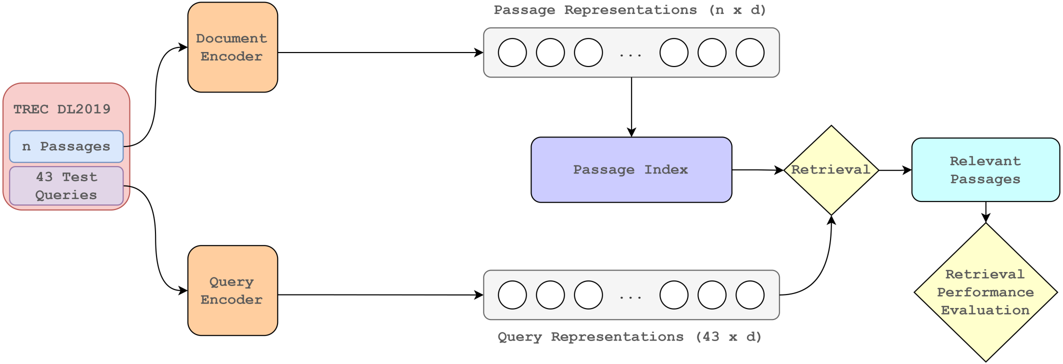
Approach – Causal Probing: Key Idea



Approach – Linear Adversarial Concept Erasure (R-LACE) [11]

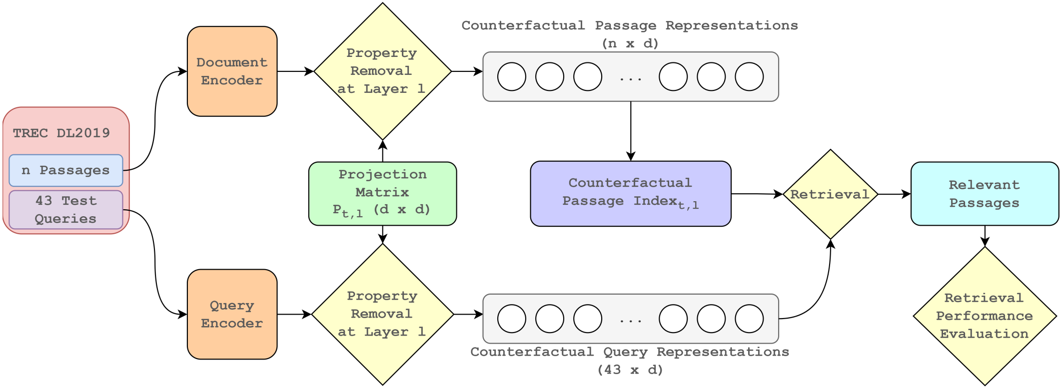
- Minimax game between two adversaries: linear predictor and a linear projection
- Goals:
  - Predictor unable to solve task in projected subspace
  - Minimal damage to unrelated information
- Input: Concept dataset, k (removed subspace rank)
- Output: Linear concept-removing projection

Approach – IR with Bi-Encoders



[12]

Approach – Causal Probing: Procedure



Approach – Investigated IR Properties

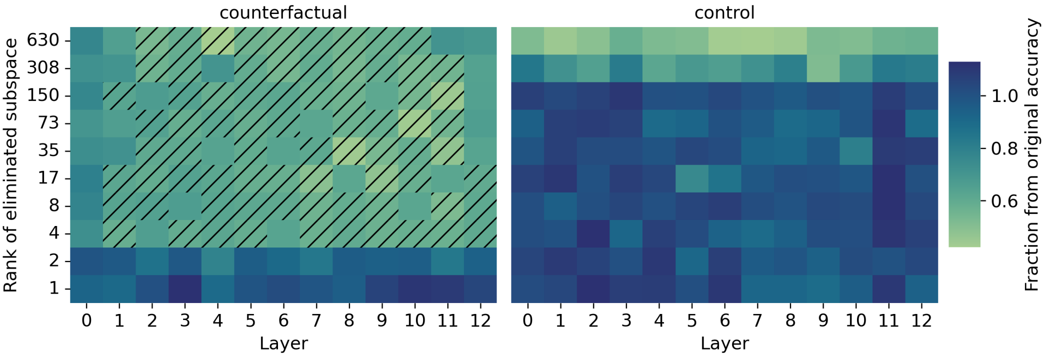
- **BM25**: exact term-matching [1] [2]
- **SEM**: Semantic similarity of query and document (cosine similarity between averaged GloVe-embeddings [13])
- **TI**: Term importance w.r.t. a query (RSJ weight) [14, 15]
- **NER**: Named-entity recognition
- **COREF**: Coreference resolution
- **QC**: Question classification

Approach – Feasibility Studies

1. Eliminating Subspaces of Increasing Ranks
   - Goals: Investigate influence of k; find the best k for each property
2. Probing as a Sanity Check
   - Goals: Confirm that properties are linearly encoded in the subject model's representations and R-LACE succesfully removes them

Results – Feasibility Study: Eliminating Subspaces of Increasing Ranks

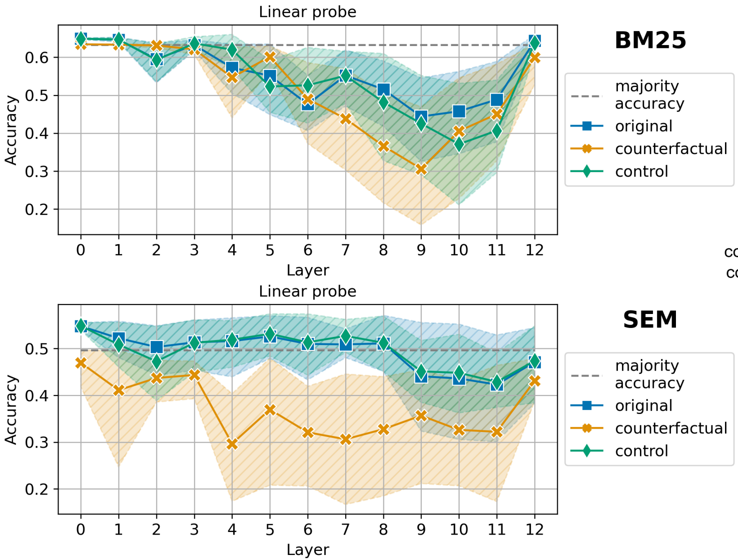
Depicted property: Question classification



Feasibility Study: Probing as a Sanity Check

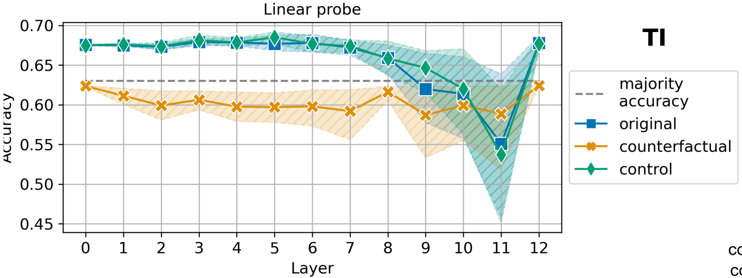
- Conventionally probe 3 kinds of representations for each property: original (fixed), counterfactual and control
- Sanity check considered passed when accuracies meet the following:
  1. original $>$ majority
  2. counterfactual $<$ original (preferably counterfactual $\leq$ majority)
  3. counterfactual $<$ control

Results – Feasibility Study: Probing as a Sanity Check (1/3)

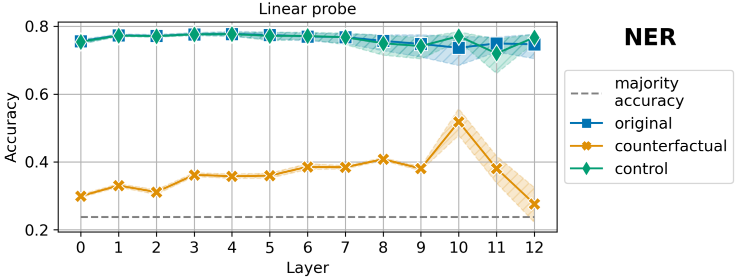


original > majority
counterfactual < original
counterfactual < control

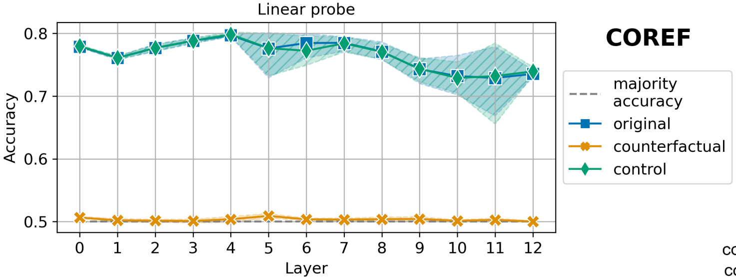
Results – Feasibility Study: Probing as a Sanity Check (2/3)



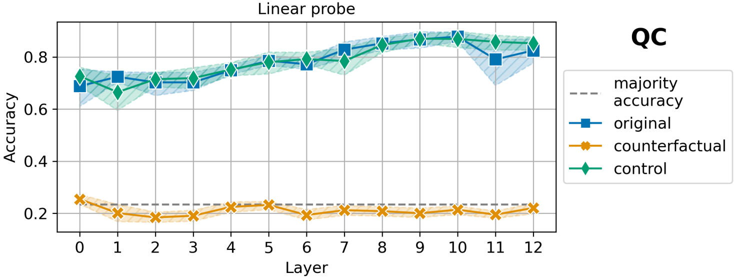
original > majority
counterfactual < original
counterfactual < control



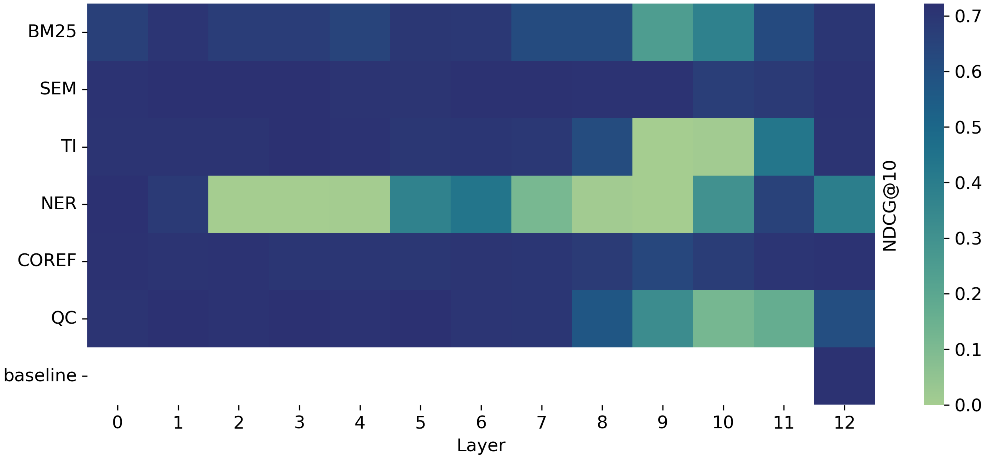
Results – Feasibility Study: Probing as a Sanity Check (3/3)



original > majority
counterfactual < original
counterfactual < control



Results – Causal Probing



Conclusion (1/2)

- **RQ1** Can we confirm the feasibility of *causally probing* our bi-encoder subject model in the context of retrieval?
  - Yes, for most of the properties. Limitations for BM25 and SEM.
- **RQ2** On which properties does our bi-encoder rely upon to solve the task of text retrieval?
  - Importance hierarchy: SEM, COREF $<$ BM25, QC $<$ TI, NER
- **RQ3** At which layers are important properties encoded?
  - Removal has larger impact at later layers, except for NER.

Conclusion (2/2)

- Limitations:
  - Only approximation of a property gets removed
  - Spurious correlations with a property
  - Only removal of linear information
- Future Work:
  - Additional properties
  - Investigate other bi-encoder architectures and training regimes
  - Use non-linear removal technique [16]
  - Use advancement of R-LACE: LEAst-squares Concept Erasure (LEACE) [17] (closed-form solution for complete linear concept erasure)

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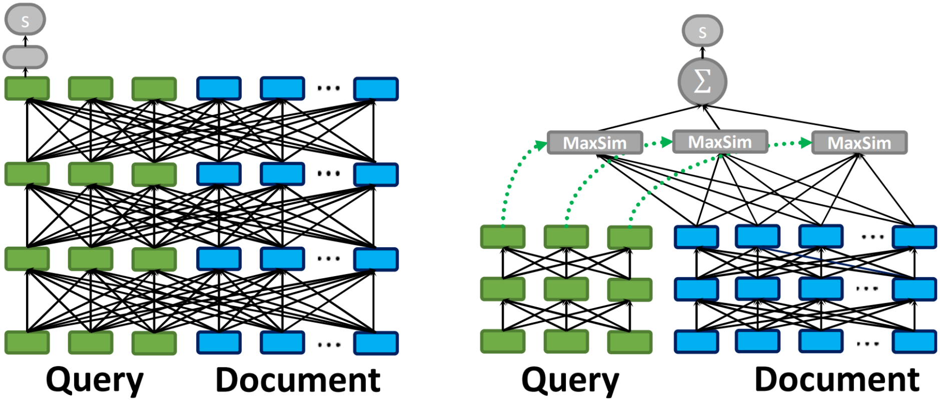
Backup Slides

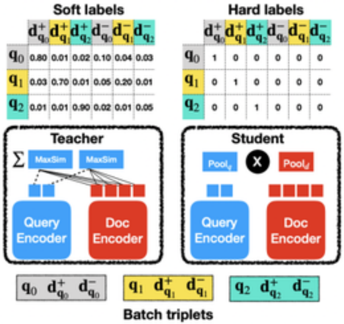
ColBERT [18]



(c) All-to-all Interaction
(e.g., BERT)

(d) Late Interaction
(i.e., the proposed ColBERT)

TCT-ColBERT [4, 5]



1. Teacher: ColBERT (BERT-based)

2. Student: BERT-based Bi-encoder with avg pooling

3. Student Training:

$$\mathcal{L} = -\sum_{i=1}^{|B|}\left\{\overbrace{\boxed{\gamma \cdot \log(P_S(d^+_{q_i}|q_i))}}^{\text{ranking loss}} + \underbrace{\boxed{(1-\gamma)\sum_{d' \in \mathcal{D}_B} KL(P_S(d'|q_i)||P_T(d'|q_i))}}_{\text{distillation loss}}\right\}$$

tight coupling: inference with the teacher while distillation, not beforehand

IR Properties – Examples

Task	Type	Level	Example
BM25	Regression	Sequence	**query**: most expensive hotels in new york city **passage**: The world's most expensive flight costs $38,000 — one way. Etihad Airways' new route connecting Mumbai and New York City... **target**: 22.063
SEM	Regression	Sequence	**query**: does insulin give you constipation **passage**: Summary: Constipation is found among people who take Insulin, especially... **target**: 0.132
AVG TI	Regression	Sequence	**query**: how long can ribs stay frozen **passage**: Raw pork chops can be safely frozen for up to six months... **target**: 2.763
TI	Regression	Token	**query**: where is hamvir's rest in skyrim **passage**: Hearthfire is the second DLC release for [**Skyrim**] behind the extremely successful... **target**: 10.336
NER	Classification	Token	**passage**: If you want to meet halfway between [**Los Angeles**], CA and Stockton, CA or just... **target**: Geopolitical entity (GPE)
COREF	Classification	Token	**passage**: [**Aluminum chloride**] is a chemical compound that has several uses, including as a treatment for excessive sweating and in antiperspirants. [**It**] is used... **target**: True
QC	Classification	Sequence	**query**: What is the full form of .com? **target**: Abbreviation (ABBR)

Linear Probe

- Binary or multinomial logistic regression model, depending on the task
- optimization goal (multinomial):

$$\min_{w,b} -\frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{K} y_{i,k} \log \frac{\exp(x_i w^{(k)} + b^{(k)})}{\sum_{j=1}^{K} \exp(x_i w^{(j)} + b^{(j)})} \tag{1}$$

NDCG

- main metric in TREC DL
- $$\mathrm{NDCG} = \frac{\mathrm{DCG}}{\mathrm{IDCG}} \tag{2}$$
- $$\mathrm{DCG} = \sum_{i=1}^{|\mathcal{C}|} \frac{y_i}{\log_2(i+1)} \tag{3}$$

Term Importance – RSJ formula [15]

$$RSJ(t, q, \mathcal{C}) = \log \frac{p(t|\mathcal{R})p(\neg t|\neg\mathcal{R})}{p(\neg t|\mathcal{R})p(t|\neg\mathcal{R})} \tag{4}$$

Causal Probing Results – Recall@1000